

Air Quality Impacts of Livestock Waste on Human Health



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1 Animal Waste Management and Its Environmental Impacts

As animal agriculture has grown in size and become geographically concentrated, policymakers have given increasing consideration to the environmental impacts of waste management at livestock facilities for dairy, swine and poultry (National Research Council, 2002). Waste by-products may cause environmental degradation throughout the animal agriculture process, from animal feeding and housing, to manure storage and land-based application of manure as a crop fertilizer. Improper management of animal waste products – comprised of manure, urine and bedding material – during these steps is the primary source of environmental degradation from animal agriculture operations (Aillery et al., 2005). Pollutants associated with animal waste products include nutrients, organic matter, pathogens, air emissions, visibility impacts and odors (Abt Associates Inc., 2000).

Animal wastes produce environmental impacts via three primary pathways: surface runoff from improper storage or over-application of manure on croplands, leaching from storage facilities and tilled soils to groundwater, and evaporation (volatilization) of gaseous compounds. A number of agricultural best management practices (BMPs) are implemented under the Chesapeake Bay Total Maximum Daily Load (TMDL)¹ allocations for sediment, nitrogen, and phosphorous; these BMPs improve manure management during these phases of waste production.

While much of these pollution reductions will be achieved via BMPs related to runoff management, practices related to air emissions are also in place and will affect the Chesapeake Bay Watershed. A recent estimate by the US EPA National Emissions Inventory finds that about 34% of the amount of nitrogen added to the Bay and its watershed on a yearly basis (loading) comes from atmospheric deposition.² States have thus planned to include a number of emissions-reducing BMPs, including those related to storage, manure amendments, and diet management/optimization. In particular, Phase II Watershed Implementation Plans (WIPs) from watershed states include the use of poultry phytase (a feed amendment), alum (a manure amendment which reduces ammonia (NH₃) volatilization), dairy precision feeding, manure transport outside of the watershed, and direct ammonia emissions reductions via bio-filters on animal housing structures and the use of manure storage lagoon covers. As ammonia emissions are a substantial component of air pollution related to animal agriculture, and have air quality impacts with great monetary value (e.g., McCubbin, Apelberg, Roe, & Divita, 2002), the rest of this report focuses on ammonia and practices which directly reduce its volatilization³.

Ammonia is a gaseous form of nitrogen, and comprises a substantial portion of the nitrogen compounds released during animal agriculture. Ammonia is produced via rapid bacterial conversion of urea excreted from cattle and hogs and uric acid from poultry. Chemical reactions in the atmosphere (among sunlight, water vapor, ammonia, products of fuel combustion, and solvents) convert ammonia to the small

¹ In response to Executive Order 13508 mandating EPA coordinate Federal and State efforts to improve water quality in Chesapeake Bay, EPA established TMDLs for nitrogen, phosphorus, and sediment for the Chesapeake Bay. These TMDLs call for reductions of 25, 24, and 20%, respectively, of these pollutants. For more information, please review: <http://www.epa.gov/chesapeakebaytmdl/>.

² US EPA. Chesapeake Bay TMDL, Section 4: Sources of Nutrients and Sediment to the Chesapeake Bay & Appendix L. Setting the Chesapeake Bay Atmospheric Nitrogen Deposition Allocations, December 29, 2010.

³ Other air emissions may be reduced as an ancillary benefit of reducing ammonia emissions. While emissions vary by livestock operation and management practices used on-site, relevant compounds are likely to include hydrogen sulfide, larger particulate matter (e.g., PM₁₀), volatile organic compounds, greenhouse gases, and odors (Cole et al., 2008).

secondary aerosol particles known as PM_{2.5} (e.g., ammonium nitrate and ammonium sulfate) (Bittman & Mikkelsen, 2009). EPA has determined that there is sufficient weight of evidence to support a causal relationship between PM_{2.5} and premature mortality, which is the most critical health effect considered in air pollutant reduction benefit analyses.⁴ In addition, the Particulate Matter Integrated Science Assessment (ISA) has determined causal or likely causal relationships between PM_{2.5} and several morbidity effects, including hospitalization for cardiovascular and respiratory diseases. Thus, reducing ammonia emissions tends to translate to substantially valuable air quality benefits (e.g., McCubbin, et al., 2002).

In this analysis, we estimate the health benefits resulting from improved air quality through BMP implementation (under the Chesapeake Bay TMDL allocations for sediment and nutrients) in 2025. We focus on PM_{2.5} reduction as a result of decreased ammonia emissions in the Chesapeake Bay states. The BMPs considered in our analysis include alum, lagoon covers and biofilters.⁵

⁴ The evidence is detailed in the ISA for each criteria air pollutant. ISAs are published on EPA's website: <http://www.epa.gov/ncea/isa/>

⁵ There are a number of other BMPs, but due to data availability for the implementation effectiveness factors, we consider only these BMPs. The more BMPs we include, the more health benefits will be generated.

Baseline Ammonia Emissions in Year 2010

In this section, we present the methodology used to estimate atmospheric ammonia emissions from animal livestock operations in the Chesapeake Bay states.

Animal livestock refers to domesticated animals intentionally reared for the production of food, fiber, or other goods or for the use of their labor. Nitrogen occurs as unabsorbed nutrients in animal feces and urine. In this report, we refer to manure as the combination of feces and urine. Ammonia is a byproduct of the decomposition of the organic nitrogen compounds in manure. The potential for ammonia emissions exists wherever manure is present, and ammonia is emitted from confinement buildings, open lots, manure storage, anaerobic lagoons, and land application with both wet and dry manure handling systems.

The methodology used in this analysis to estimate livestock ammonia emissions is based on the methods presented in the EPA report entitled, “National Emission Inventory – Ammonia Emissions from Animal Agricultural Operations”, April 2005 (U.S. EPA, 2005a). This report provided ammonia emission factors and manure management train (MMT) data needed to estimate ammonia emissions for the Chesapeake Bay watershed.⁶ Other data needed to estimate emissions included county-level animal population data and information on BMPs to reduce nutrient loadings to the Chesapeake Bay, which were provided by EPA’s Chesapeake Bay Program Office (CBPO) through communications with Jeff Sweeney.

1.1 Method

Abt Associates estimated 2010 ammonia emissions from agricultural livestock in the Chesapeake Bay watershed by multiplying livestock activity data (expressed in terms of the number of heads of each livestock category in each U.S. county) by NH₃ emission factors.

The approach to calculating NH₃ emissions for animal livestock operations consists of four general steps, as follows:

- Determine county-level population of animals for 2010.
- For each state, apportion the animal populations of beef, dairy, poultry, and swine to one of the manure management trains (MMT).
- Assign emission factors obtained from the literature to each animal type and MMT.
- Calculate ammonia emissions based on county-level animal populations and emission factors.

1.2 Activity Data - Animal Populations

EPA’s CBPO provided the county level activity data (i.e., animal population head counts) for the Chesapeake Bay watershed states – Delaware, Maryland, New York, Pennsylvania, Virginia, and West Virginia (based on the CBPO Watershed Model, April 2012). Table 2-1 summarizes the animal head counts in the Chesapeake Bay Watershed for the livestock categories for which we estimated NH₃ emissions (state-level animal head counts are presented in Appendix A).

Because we assumed that BMPs to control nutrient loadings apply only to animals that are raised within the Chesapeake Bay Watershed, two sets of animal counts were provided by CBPO for each county: (1) the number of heads within the Chesapeake watershed and (2) the number of heads outside of the Chesapeake watershed.

⁶ An MMT consists of an animal confinement area (e.g., drylot, pasture, flush, scrape); components used to store, process, or stabilize the manure (e.g., anaerobic lagoons, deep pits); and a land application site where manure is used as a fertilizer source.

We apportioned the county-level animal numbers to MMTs based on state-level MMT percentages obtained from Appendix C of EPA (2005a). We did not apportion populations of ducks, geese, goats, horses, and sheep to MMTs because all MMTs for each of these livestock categories use one **emission** factor. For cattle reported as “Other Cattle” by CBPO, we equally divided them between dairy cattle and beef cattle at the county-level. Appendix A provides details on the MMT components for each animal type and MMT distributions by state. The MMT developed distributions were based on manure management system data obtained for the U.S. Greenhouse Gas Inventory (U.S. EPA, 2002).

Table 2-1: Animal Population by Livestock Category for the Chesapeake Bay States

Livestock Categories	Animal Population
Angora Goats	3,467
Beef	715,214
Broilers	225,179,178
Dairy	1,009,641
Hogs and pigs for breeding	141,184
Hogs for slaughter	1,415,321
Horses	452,297
Layers	30,304,947
Milk goats	24,205
Other Cattle	1,671,913
Pullets	9,411,330
Sheep and lambs	156,256
Turkeys	17,509,630

Source: Obtained from EPA's CBPO (CBPO Watershed Model, April 2012).

1.3 **Emission** Factors

Annual average livestock **emission** factors for each livestock category and MMT are provided in Table 2-2 (TranSystems|E.H. Pechan, 2012; U.S. EPA, 2005a, Appendix D). For this study, we used **emission** factors based on pounds of ammonia emitted per head (lbs NH₃/year/head). The **emission** factors for most categories and the data sources are provided in Appendices D and A, respectively, of EPA (2005a). We obtained **emission** factors for angora goats, hogs and pigs for breeding, horses, milk goats, lamb and sheep from a report supporting the development of the National Emissions Inventory (TranSystems, 2010).

Table 2-2: Livestock **Emission Factors**

Livestock Category	Manure Management Train	Emission Factor ¹	Reference
Angora Goats	All	13.97	TranSystems (2010)
Beef	Feedlot	28.60	EPA (2005a)
Beef	Pasture/Range	23.81	EPA (2005a)
Broilers	House and Outdoor Confinement	0.22	EPA (2005a)
Dairy	All	27.80	EPA (2005a)
Hogs and Pigs for Breeding	All	13.70	TranSystems (2010)
Hogs for Slaughter	Houses with Lagoons	6.00	EPA (2005a)

Hogs for Slaughter	Houses with Lagoons and Solid Sep	6.80	EPA (2005a)
Hogs for Slaughter	Deep Pit	7.60	EPA (2005a)
Hogs for Slaughter	Pasture	18.30	EPA (2005a)
Horses	All	28.60	TranSystems (2010)
Layers	Dry Layers	0.42	EPA (2005a)
Layers	Wet Layers	0.24	EPA (2005a)
Milk Goats	All	13.97	TranSystems (2010)
Pullets	All	0.22	EPA (2005a)
Sheep and Lamb	All	7.00	TranSystems (2010)
Turkeys	All	1.12	EPA (2005a)

1. The unit for the **emission** factors is: lbs NH₃/yr/head.

1.4 Sample Calculation

To illustrate, we provide below a sample calculation for Hogs for Slaughter, Houses with Lagoons in Kent County, Delaware.

- Total number of hogs for slaughter in Kent County, Delaware = 278
 - 102 hogs in the Chesapeake Bay Watershed
 - 176 hogs outside the Chesapeake Bay Watershed
- MMT percentages and **Emission** Factors
 - Houses with Lagoons = 20%, that is, 20% of the hogs for slaughter were kept in houses with lagoons.
 - Ammonia Emissions Factor = 6.00 lbs NH₃/yr/head
- In the Chesapeake Bay Watershed, NH₃ emissions associated with hogs for slaughter in Houses with Lagoons = 102 hogs × 0.20 Hogs in Houses in Lagoons × 6.00 lbs NH₃/yr/head = 122.4 lbs NH₃ per year
- Out of the Chesapeake Bay Watershed, NH₃ emissions associated with hogs for slaughter in Houses with Lagoons = 176 hogs × 0.20 Hogs in Houses in Lagoons × 6.00 lbs NH₃/yr/head = 211.2 lbs NH₃ per year

The emissions for each of the other MMTs are calculated in the same way. Table 2-3 presents the calculations of total emissions from hogs for slaughter for Kent County, Delaware. Total state-level emissions are presented in Section 5.

Table 2-3: Sample Calculation of Emissions from Hogs for Slaughter in Kent County, DE

Manure Management Train (MMT)	MMT Distribution in DE	Emission Factor (lbs NH ₃ /yr/head)	Emissions in Chesapeake Bay Watershed (CBW)	Emissions Outside CBW
	(A)	(B)	(A x B x 102) ¹	(A x B x 176) ²
Houses with Lagoons	20%	6	122.4	211.2
Houses with Lagoons and Solid Sep	5%	6.8	34.7	59.8
Deep Pit	74%	7.6	573.6	989.8
Pasture	1%	18.3	18.7	32.2
Total	100%	-	749.4	1,293.1

1. Based on a total of 102 hogs for slaughter in the CBW in Kent County, DE.
2. Based on a total of 176 hogs for slaughter outside the CBW in Kent County, DE.

2 BMPs to Control Ammonia Emissions in the TMDL Control Scenario

As described in Section 1, we consider three BMPs that comprise the TMDL control scenario in this analysis (i.e., a combination of alum, lagoon covers, and biofilters). We describe these BMPs in Section 3.1 below. Section 3.2 provides information on **emission** calculation for the control scenario.

2.1 BMPs to Control Ammonia Emissions

- Aluminum sulfate (alum) is a chemical additive applied to poultry litter. Applications reduce ammonia volatilization by acidifying the litter, which maintains ammonia in its non-volatilized form (ammonium). In addition to this air quality benefit, alum amendments reduce pathogens in poultry litter and change the properties of poultry litter such that phosphorous runoff is reduced when the litter is applied to fields as a fertilizer (Moore, n.d.).
- Biofilters are an air bio-filtration system designed to prevent or minimize odor and other emissions from enclosed or confined poultry and livestock (e.g., swine and cattle) production facilities and manure storage houses. Biofilters work by passing air through a system comprised of mechanical ventilation, ductwork and a bed of organic material that supports a microbial population. The microbial population oxidizes volatile organic compounds into carbon dioxide, water and inorganic salts (Meisinger, Simpson, & Weammert, n.d.).
- Lagoon covers reduce ammonia volatilization by creating a physical barrier between the atmosphere and the volume of liquid manure in a storage lagoon. Covers are made of permeable fiber and placed over liquid storage lagoons, thereby reducing wind velocity at the surface of the lagoon, and reducing radiation onto the lagoon surface (Meisinger, et al., n.d.). Emissions reductions stem from the resulting lower temperatures in the lagoon, and the reduced volume of manure exposed to the air. Lagoon covers can be applied to any liquid manure storage facility.

2.2 Ammonia Emissions in the TMDL Control Scenario in Year 2025

The TMDL control scenario includes implementation of alum, lagoon covers, and biofilters, where alum is applied for poultry and lagoon covers and biofilters are applied for all types of animals. To estimate ammonia emissions for the TMDL control scenario, we use

- The percentage of controlled animal units (% AU) in 2025, which is the portion of the total animal units to which the BMP is applied; and
- BMP effectiveness rate (% reduction) in 2025, which is the percent by which NH₃ emissions can be reduced due to the implementation of the BMP

See Appendix A for the percentages of controlled animal units and BMP effectiveness rates for each state in the Chesapeake Bay Watershed.

Ammonia emissions for the TMDL control scenario can then be calculated as follows. The results are presented in Section 5.1.

$$\begin{aligned}\text{Control scenario emissions} &= \text{emissions from controlled AU} + \text{emissions from uncontrolled AU} \\ &= \text{Baseline emissions} \times [\% \text{AU} \times (1 - \% \text{reduction}) + (1 - \% \text{AU})] \\ &= \text{Baseline emissions} \times (1 - \% \text{AU} \times \% \text{reduction})\end{aligned}$$

where Baseline emissions are described in Section 2.

3 Estimation of PM_{2.5} Concentration and Health Effects

We used the Co-Benefits Risk Assessment (COBRA) Model (version 2.61, released in July 2013) to estimate air quality changes and the corresponding changes in incidence of health effects from implementation of animal waste BMPs to control ammonia emissions in the Chesapeake Bay watershed. COBRA is a screening tool that provides preliminary estimates of the effects of air pollutant **emission** changes on ambient air concentrations of particulate matter (PM), translates the estimated changes in ambient PM concentrations into the number of avoided adverse health effects, and then provides a monetary value of the avoided health effects. The following sections describe the air quality modeling, customized COBRA runs, and health effect estimation.

3.1 Air Quality Modeling in COBRA

COBRA estimates particulate matter levels using the Phase II Source-Receptor (S-R) Matrix. The S-R Matrix consists of fixed transfer coefficients that reflect the relationship between annual average PM_{2.5} concentration values at a single receptor in each county (a hypothetical monitor located at the county centroid) and the contribution by PM_{2.5} species to this concentration from each **emission** source (E.H. Pechan & Associates Inc., 1994).

Because of the limited validation studies of the S-R Matrix, it should be treated as a screening tool that provides a crude estimate of the likely effect of a change in ammonia emissions on ambient PM_{2.5} levels. More sophisticated atmospheric dispersion models should be used to obtain detailed estimates of ambient air quality changes resulting from implementation of animal waste BMPs in the Chesapeake Bay watershed. For more details about the S-R matrix and its implementation in COBRA, refer to the COBRA User Manual Appendix A.⁷

3.2 Customization of COBRA Runs

COBRA has its own built-in **emission** baseline for the 2017 modeling year (see COBRA User Manual Appendix A), which is hard-coded and cannot be modified easily. We estimate air quality improvements and health benefits associated with reduced ammonia emissions from animal waste based on the baseline scenario for the Chesapeake Bay in 2025 (Chesapeake Bay baseline) and the scenario corresponding to the full implementation of the Chesapeake Bay TMDL in 2025 (TMDL control scenario). Both the baseline and control scenario emissions are based on 2010 animal population counts, as presented in Section 2.2; we are thus assuming that the 2010 counts do not change over time and can be used to estimate emissions in 2025.

Using the Chesapeake Bay baseline and the TMDL control scenario, we proceeded through the following steps in COBRA:

- Treat the Chesapeake Bay baseline as a COBRA control scenario. Specifically, we created a new scenario in COBRA for states in the Chesapeake Bay watershed: Delaware, District of Columbia, Maryland, New York, Pennsylvania, Virginia, and West Virginia. For each county in these states, COBRA expects **emission** changes between the the Chesapeake Bay baseline and the COBRA baseline (i.e., **emission** changes #1 entered into COBRA (in tons) = Chesapeake Bay baseline – COBRA baseline). In this analysis, we assumed that only emissions in the source

⁷ The user manual and other COBRA-related information can be found on <http://www.epa.gov/statelocalclimate/resources/cobra.html>

category: “Miscellaneous – Agriculture & Forestry – Agricultural Livestock” are changed due to implementation of animal waste BMPs. This category corresponds to Tier 14-01-02.⁸

- Repeat the above for the TMDL scenario corresponding to implementation of animal waste management BMPs under the TMDL program, i.e.,
 - Emission changes #2 = TMDL Control Scenario – COBRA baseline
- Obtain results by canceling out COBRA baseline effects for air quality, health effects, and monetized health benefits. We did this using SAS.
 - Benefits due to TMDL program implementation = Results from COBRA run using emission changes #2 – Results from COBRA run using emission changes #1
- Use two discount rates: 3% and 7%; so in total we made four COBRA runs.

Note that COBRA allows us to conduct baseline and control analyses for 2017 only. Therefore, the outputs from the COBRA analyses represent the benefits estimates if the TMDL program were implemented in 2017. However, since our TMDL control scenario occurs in 2025, we needed to adjust the COBRA estimates for 2017 to reflect 2025 conditions. The time-varying components of the COBRA benefits estimates are: county-level population, health effects estimates based on willingness-to-pay (WTP) measures, health effects incidence rates, and weekly wages used to value the health effect of lost work days (see Section 4.3 for details on health effects in COBRA). We addressed these differences between 2017 and 2025 as follows:

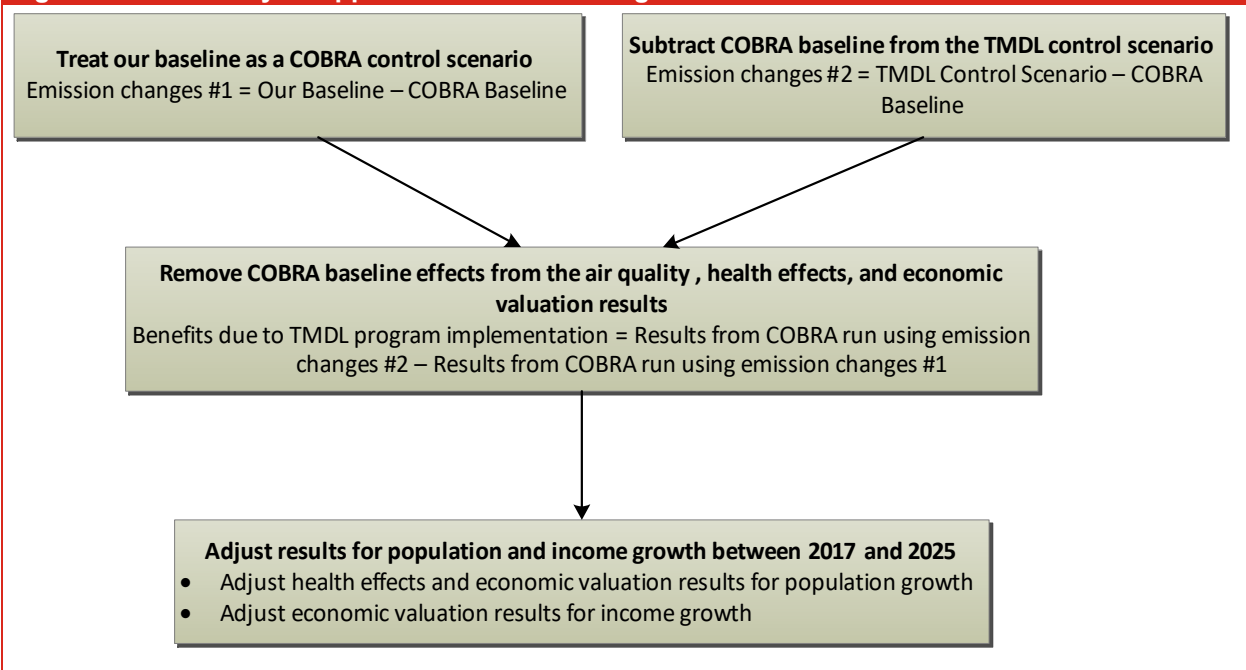
- **Population:** We used Woods & Poole’s county-level population growth projections for 2017 and 2025 to calculate population growth factors (i.e., county-specific ratios of 2025 population to 2017 population) (Woods & Poole Economics Inc., 2011). We used these factors to adjust the health effects results (both incidence and economic values) at the county level. We summed the county-level results to obtain state-level estimates.
- **WTP Measures:** Most of the health effects estimates are based on WTP or cost-of-illness (COI) estimates. According to economic theory, WTP for most goods (such as health risk reductions) will increase if real incomes increase. Therefore, COBRA includes income growth adjustment to 2017 (see details on these growth factors in Appendix B). To obtain results for 2025, we used income growth factors for 2025 to further adjust the economic valuation outputs (outside COBRA) to 2025 income levels. Since there are not sufficient data on the relationship between COI and income, we did not adjust the COI-based benefit estimates for income growth.
- **Incidence Rates for Health Effects:** All incidence rates are likely to change over time. We used projected mortality rates for 2020 in this analysis (see details on forecasting mortality rates in Appendix B). Since there is limited information on forecasted incidence rates for morbidity incidence rates, we did not account for their changes in this analysis (e.g., hospitalization and ER rates are for year 2007). Details of morbidity incidence rates are also included in Appendix B. If morbidity incidence rates decrease over time, benefits may be overstated.
- **Weekly Wages:** Weekly wages are also likely to change. However, EPA uses the Bureau of Labor Statistics’ estimate of weekly wages from 2000 in version 2.61 of the COBRA model (the most recent version available at the time of this analysis). Therefore, we also used wage value based on 2000 data, which COBRA inflated to 2010 dollars.

Figure 4-1 summarizes the approach for customizing COBRA runs, which included canceling out the

⁸ The source category codes (SCC) included in Tier 14-01-02 include poultry, cattle, hogs, dairy, horses, sheep and lambs, and goats (<http://www.epa.gov/ttnchie1/net/2002inventory.html>).

effects of COBRA's built-in baseline.

Figure 4-1: Summary of Approach for Customizing COBRA Runs



3.3 Estimation and Valuation of Avoided Adverse Health Effects

3.3.1 Estimation of Adverse Health Effects

A reduction in ambient PM_{2.5} levels is associated with reductions in a number of adverse health effects, or “health endpoints.” The concentration response (C-R) functions in the COBRA model were prepared by Abt Associates in close consultation with EPA and rely on an up-to-date assessment of the published scientific literature (e.g., U.S. EPA, 2006, 2009) to ascertain the relationship between particulate matter and the following adverse human health effects:

- Adult mortality;
- Non-fatal heart attacks;
- Infant mortality;
- Respiratory-related hospitalizations;
- Cardiovascular-related hospitalizations;
- Acute bronchitis;
- Upper respiratory symptoms;
- Lower respiratory symptoms;
- Asthma-related emergency room visits;
- Minor restricted activity days (i.e., days on which activity is reduced, but not severely restricted);
- Work days lost due to illness; and
- Asthma exacerbations (i.e., shortness of breath, wheeze, and cough in asthmatic individuals).

One of the most common C-R functional forms relating criteria air pollutants to population incidence of

an adverse health effect is log-linear (or exponential) in form:⁹

$$y = \alpha * e^{\beta x} \quad (4-1)$$

where x is the ambient air pollutant concentration (PM_{2.5} in this analysis), y is the incidence of the adverse health effect corresponding to x , β is the coefficient of ambient concentration of the air pollutant (describing the extent of change in y with a unit change in x), and the parameter α is the incidence when there is no ambient air pollutant. Each epidemiological study provides b (an estimate of β).

Let x_0 denote the baseline (upper) level of the ambient air pollutant and x_1 denote the “control scenario” (lower) level. In addition, let y_0 denote the baseline incidence of the health effect (corresponding to the baseline ambient pollutant level, x_0) and y_1 denote the incidence after the regulatory scenario is implemented, corresponding to ambient pollutant level, x_1 . Equation (4-1) and the estimate, b , can be used to derive the following estimated relationship between the absolute reduction in ambient air pollutant level, $\Delta x = (x_0 - x_1)$, and the corresponding reduction in health effect incidence, Δy :

$$\Delta y = (y_0 - y_1) = y_0 \cdot (1 - e^{-b \Delta x}) \quad (4-2)$$

Using COBRA, we estimated the reductions in incidence of each adverse health effect in each county in the coterminous U.S. due to the air quality changes. We also aggregated the incidence results to the national level by summing the health effect-specific incidence results for each county. Since the C-R functions are continuous and have no thresholds, even very small reductions in PM_{2.5} lead to a reduction in incidence of the associated adverse health effects. See Appendix B for details on the C-R functions.

Key details of the incidence rates in COBRA include:

- County-level mortality rates are based on 2004-2006 CDC data. They were projected to 2020 using projected life tables from the U.S. Census Bureau.
- Incidence rates for other health endpoints are not projected. COBRA uses historical data for various years.

See Appendix B for further details on incidence rates in COBRA.

3.3.2 Valuation of Avoided Mortality and Morbidity

We also used COBRA to value the avoided cases of adverse health effects.¹⁰ The value of cases of an adverse health effect avoided in a given year is calculated by multiplying the number of avoided cases of the health effect in that year by the value per case (the unit value). This section briefly describes the valuation methods used in COBRA.

Where possible, we based unit values on willingness to pay (WTP) studies. For those health effects (e.g., hospital admissions for respiratory illnesses) for which WTP estimates are not available, we estimated unit values using cost-of-illness (COI), i.e., the medical and opportunity costs of treating and/or mitigating the effect, as a proxy for WTP.

We chose the unit value for premature mortality based on a “value of statistical life” (VSL) of \$6.3 million (in year 2000\$, assuming 1990 income levels); this value has been used in recent OAQPS benefits analyses. This estimate is the mean of a distribution fitted to 26 VSL estimates that appear in the

⁹ The exception in this analysis is for respiratory symptoms and illnesses. The C-R functions for respiratory symptoms and illnesses are logistic in form.

¹⁰ Detailed descriptions of valuation are given in Appendix F of the COBRA User Manual, available online at: <http://epa.gov/statelocalclimate/documents/pdf/cobra-2.61-user-manual-july-2013.pdf>.

economics literature and that have been identified in the Section 812 Report to Congress as “applicable to policy analysis.”

As noted above, we estimated unit values for hospital admissions endpoints using COI. This approach is consistent with recent RIAs conducted by OAQPS (e.g., U.S. EPA, 2008). Estimates of the medical expenditures and opportunity costs associated with hospitalizations are based on illness-specific mean hospital charges and mean lengths of stay (LOS) obtained from the Agency for Healthcare Research and Quality (Agency for Healthcare Research and Quality, 2007).¹¹ The opportunity cost of a hospital stay is estimated as the product of lost daily wage and mean LOS. COI estimates generally understate the true social cost of a health effect, because they do not include the WTP to avoid the pain and suffering associated with the illness, which is often substantial (Berger, Blomquist, Kenkel, & Tolley, 1987; Harrington & Portney, 1987).

Economic theory argues that WTP for most goods will increase if real income increases. Some WTP-based unit values used in this analysis are based on valuation studies conducted in the late 1980s and early 1990s. Because real income has grown since the studies were conducted, and will likely continue to grow in the future, WTP for changes in the risk of premature death and disease in the years of interest (i.e., the years over which mortality is projected to occur) will likely be greater than the WTP estimates reported in the underlying studies used in this analysis. Therefore, COBRA has done income growth adjustment to 2017 (as the model default), to take into account increases in real income over time. In order to adjust income growth to 2025 income level, we manually made the adjustment outside COBRA using income growth factors for 2025 (see Appendix B for details about developing income growth factors). We did not adjust COI-based estimates for projected changes in income because the COI method estimates the direct cost of a health outcome.

We inflated unit values calculated for earlier years to year 2010 dollars, using the consumer price index for urban consumers (CPI-U) for All Items for WTP estimates,¹² the CPI-U for medical care¹³ for the medical expenditures portion of COI estimates, and the Bureau of Labor Statistics Employment Cost Index for Wages & Salaries¹⁴ for the opportunity cost portion of COI estimates.

All unit values in this analysis are based on a projected 2025 income level and are in 2010\$. Table 4-1 shows the unit values used in COBRA, adjusted for income growth to 2025, and indicates the type of value: VSL, COI, or WTP.

Table 4-1: Unit Values for Economic Valuation of Health Endpoints (2010 \$)

Health Endpoint	Age Range	Type of Value (VSL, WTP or COI)	Unit Value (2025 Income Level)	
			3% DR	7% DR
Mortality ^a	25 – 99	VSL	\$8,863,205	\$7,894,316
Infant Mortality ^b	0 – 0	VSL	\$9,879,048	\$9,879,048
Acute Myocardial Infarction, Nonfatal ^c	0 – 24	COI	\$33,259	\$31,446

¹¹ Data are from the 2007 AHRQ’s Healthcare Utilization Project (HCUP) National Inpatient Sample (NIS) database.

¹² Available online at: <http://data.bls.gov/cgi-bin/surveymost?cu>

¹³ Available online at: <http://data.bls.gov/cgi-bin/surveymost?cu>

¹⁴ Available online at: <http://research.stlouisfed.org/fred2/data/ECIWAG.txt>

Acute Myocardial Infarction, Nonfatal ^c	25 – 44	COI	\$45,085	\$42,033
Acute Myocardial Infarction, Nonfatal ^c	45 – 54	COI	\$50,689	\$47,050
Acute Myocardial Infarction, Nonfatal ^c	55 – 64	COI	\$134,003	\$121,641
Acute Myocardial Infarction, Nonfatal ^c	65 – 99	COI	\$33,259	\$31,446
Acute Myocardial Infarction, Nonfatal ^d	0 – 24	COI	\$163,051	\$163,051
Acute Myocardial Infarction, Nonfatal ^d	25 – 44	COI	\$174,876	\$173,638
Acute Myocardial Infarction, Nonfatal ^d	45 – 54	COI	\$180,480	\$178,655
Acute Myocardial Infarction, Nonfatal ^d	55 – 64	COI	\$263,795	\$253,247
Acute Myocardial Infarction, Nonfatal ^d	65 – 99	COI	\$163,051	\$163,051
HA, All Cardiovascular (less AMI)	18 – 64	COI	\$41,002	\$41,002
HA, All Cardiovascular (less AMI)	65 – 99	COI	\$38,618	\$38,618
HA, All Respiratory	65 – 99	COI	\$32,697	\$32,697
HA, Asthma	0 – 17	COI	\$15,430	\$15,430
HA, Chronic Lung Disease	18-64	COI	\$20,349	\$20,349
Asthma ER Visits (Smith et al. (1997)	0 – 99	COI	\$464	\$464
Asthma ER Visits (Stanford et al. (1999)	0 – 99	COI	\$388	\$388
Acute Bronchitis	8 – 12	WTP	\$485	\$485
Lower Resp. Symptoms	7 – 14	WTP	\$21	\$21
Upper Resp. Symptoms	9 – 11	WTP	\$34	\$34
MRAD	18 – 64	WTP	\$69	\$69
Work Loss Days	18 – 64	WTP	\$151	\$151
Asthma Exacerbation (Cough, Shortness of Breath, or Wheeze)	6 – 18	WTP	\$58	\$58

NOTE: ^a Mortality value after adjustment for 20-year lag.

^b Infant mortality value is not adjusted for 20-year lag.

^c Based on Russell (1998)

^d Based on Wittels (1990)

In some cases there are multiple valuations available for a health effect, with no one valuation clearly superior to another. In such cases we used a pooled value.

- Smith et al. (1997) and Stanford et al. (1999) both evaluate asthma emergency room (ER) visits using COI. Following EPA, we assigned equal weight to each study (i.e., 0.5) and COBRA then used the weighted average to value ER visits.

- To value Acute Myocardial Infarction, we pooled Russell (1998) and Wittels (1990) by assigning equal weight (i.e., 0.5) to each.

We calculated the monetized benefit associated with each health effect for the Chesapeake Bay airshed by summing the benefits associated with the health effect across all affected counties.

Because economic valuation of air pollutant removal impact on human health uses the same unit of measure (i.e., dollars) for all health effects, these values can be aggregated across (non-overlapping) health effects. Thus, we also calculated the national-level benefits associated with all health benefits included in the analysis. Most health effects and their benefits occur in the year of the analysis (i.e., 2025). Mortality benefits were assumed to occur over 20 years.¹⁵ Non-fatal heart attacks occur in the year of analysis but avoided costs continue for 5 years. All benefits are expressed in 2010 dollars. Benefits correspond to one year (2025) of PM_{2.5} changes and are based on 2025 income and population levels. This analysis does not account for the TMDL implementation schedule before 2025, for future stream of benefits resulting from reduced PM_{2.5} concentrations after 2025, or the time needed for full TMDL implementation.

4 Results

4.1 Ammonia Emission Changes

The number of animals and the ammonia emissions changes under the control scenario are presented by livestock group in Table 5-1. Three of the livestock groups in this table consist of multiple livestock categories. Specifically, “goats” include angora goats and milk goats; “poultry” includes broilers, layers, pullets, and turkeys; and “hogs and pigs” includes hogs and pigs for breeding and hogs for slaughter. As shown in Table 5-1, the 2025 TMDL control scenario results in ammonia emissions reductions for all states in the Chesapeake Bay Watershed except West Virginia.

Table 5-1: Summary of Animal Counts and Ammonia Emissions Changes in 2025 under the TMDL Scenario

State / Livestock Group ^{1,2}	Count	Baseline Emissions (in tons)	Reduction in Emissions under the TMDL Scenario (in tons)
Delaware			
Beef	3,634	51.9	1.3
Dairy	6,211	86.3	2.3
Goats	460	3.2	0.1
Hogs and pigs	2,673	14.7	0.4
Horses	21,300	304.6	6.7
Other cattle	9,600	84.5	2.2
Poultry	54,071,744	6,057.6	180.6
Sheep and lambs	869	3.0	0.1
Maryland			
Beef	43,835	618.0	0

¹⁵ Current EPA benefits analyses (U.S. EPA, 2006, p. 5-21) assume a 20-year lag structure, with 30 percent of premature deaths occurring in the first year, 50 percent occurring evenly over years 2 to 5 after the reduction in PM_{2.5}, and 20 percent occurring evenly over years 6 to 20 after the reduction in PM_{2.5}.

Dairy	49,496	688.0	0
Goats	3,694	25.8	0
Hogs and pigs	19,887	79.7	0
Horses	86,517	1,237.2	0
Other cattle	79,887	692.4	0
Poultry	72,194,010	8,301.6	1,665.3
Sheep and lambs	21,688	75.9	0
New York			
Beef	51,193	726.3	0
Dairy	393,398	5,468.2	0
Goats	3,923	27.4	0
Hogs and pigs	25,423	98.3	0
Horses	52,584	752.0	0
Other cattle	316,202	2,814.2	0
Poultry	1,596,577	293.9	0
Sheep and lambs	27,567	96.4	0
Pennsylvania			
Beef	96,756	1,365.1	16.5
Dairy	475,038	6,603.0	83.4
Goats	12,505	87.3	0.9
Hogs and pigs	1,261,510	4,943.6	66.7
Horses	147,757	2,112.9	24.4
Other cattle	750,658	6,342.1	80.4
Poultry	62,641,836	10,795.2	288.1
Sheep and lambs	60,059	210.1	2.5
Virginia			
Beef	443,959	6,331.6	0
Dairy	80,818	1,123.4	0
Goats	5,648	39.4	0
Hogs and pigs	244,603	928.0	0
Horses	135,990	1,944.7	0
Other cattle	437,971	3,547.3	0
Poultry	74,215,188	13,670.3	2,951.7
Sheep and lambs	32,904	115.1	0
West Virginia			
Beef	75,837	1,081.2	0
Dairy	4,680	65.1	0
Goats	1,442	10.1	0
Hogs and pigs	2,409	9.7	0
Horses	8,149	116.5	0
Other cattle	77,595	683.1	0
Poultry	17,685,730	2,818.8	0
Sheep and lambs	13,169	46.1	0

1. The District of Columbia is not included in this table because it has no animals and no ammonia emission changes.

2. Three of the livestock groups in this table consist of multiple livestock categories. Specifically, goats include angora goats and milk goats. Poultry includes broilers, layers, pullets, and turkeys. Hogs and pigs include hogs and pigs for breeding and hogs for slaughter.

4.2 Air Quality Changes

The average reduction in PM_{2.5} in each affected state is presented in Table 5-2, for the control scenario. In addition to states in the Chesapeake Bay Watershed, 11 other states experience PM_{2.5} reductions under the control scenario because NH₃ emission reductions in nearby states reduce their ambient PM_{2.5} concentrations due to air pollution transport effects. The District of Columbia has the highest average baseline concentration of PM_{2.5}, followed by Maryland. These states also experience the greatest reductions in PM_{2.5} for the control scenario. COBRA predicted no air quality changes in Delaware, even though small emission reductions were observed. This is likely because either: (1) the S-R matrix is not sensitive enough to pick up such small NH₃ emissions changes; or (2) there is an excess amount of atmospheric ammonia and therefore small NH₃ reductions do not affect the formation of atmospheric ammonium sulfate or ammonium nitrate, which contribute to PM_{2.5}.

Table 5-2: Summary of Air Quality Results for the 2025 TMDL Scenario

State	Average Baseline PM _{2.5} (ng/m ³)	Average Reduction in PM _{2.5} under the TMDL Scenario (ng/m ³)
Chesapeake Bay Watershed		
Delaware	8,473	0
District of Columbia	16,004	38
Maryland	10,656	7
New York	7,402	3
Pennsylvania	8,415	1
Virginia	9,711	>0
West Virginia	8,883	3
Outside Chesapeake Bay Watershed¹		
Alabama	10,097	>0
Connecticut	8,293	5
Florida	9,231	>0
Georgia	11,384	>0
Louisiana	8,413	>0
Maine	4,183	1
Massachusetts	8,331	3
New Hampshire	6,287	3
New Jersey	10,359	1
Rhode Island	7,138	4
Vermont	5,224	1

1. In addition to states in the Chesapeake Bay Watershed, 11 other states experience PM_{2.5} reductions under the TMDL scenario. Specifically, as a result of air pollution transport effects, NH₃ emission reductions in the Chesapeake Bay Watershed reduces the other states' ambient PM_{2.5} concentrations. Some of these states experience very small PM_{2.5} reductions that result in significant health benefits for the affected population.

4.3 Health Effects

Health effects results are summarized in Table 5-3 below (see Appendix C for detailed results). The results correspond to one year of emission reduction (2025). Although pollutant reductions are estimated

for one year only (2025) not all avoided cases of adult mortality are expected to occur in the analysis year. Following SAB guidance, the standard EPA benefit analysis assumes that only a part of the estimated number of avoided deaths that are attributable to a reduction in emissions in a given year will occur in that year (U.S. EPA, 2006, p. 5-21).¹⁶ In addition, while all avoided cases of non-fatal heart attacks are assumed to occur in the year of analysis, their benefits are accrued over multiple years.

We discounted benefits that occur after the year of the analysis to year 2025 using 3% and 7% discount rates. Thus, while the monetized benefits for many health effects are the same under both discount rates, the values of adult mortality and non-fatal heart attacks vary by discount rate.¹⁷ Since the value of mortality reductions is much higher than the value of other avoided health effects, a majority of the monetized benefits for each control scenario consists of the value of avoided adult mortality; the number of avoided infant mortalities is very small in each control scenario, so they do not contribute a large amount to the total monetized benefits. Note that no health benefits are accrued in Delaware, since there are no changes in PM_{2.5} in this state.

The results of implementing the TMDL program in 2025 are presented in Table 5-3. Although some benefits of reducing PM_{2.5} occur in future years (e.g., some mortality cases) these results represent one year of PM_{2.5} reduction. The avoided cases for the total health effects (both morbidity and mortality) are “N/A” because it is not appropriate to sum the incidence across different health effects. The total value of all avoided health effects ranges from \$153.3 million to \$346.4 million (using a 3% discount rate), while the total value of reductions in adult mortality ranges from \$150.8 million to \$342.0 million (using a 3% discount rate). Using a 7% discount rate, the total value of avoided health effects ranges from \$136.8 million to \$308.9 million, and the total value of reductions in adult mortality ranges from \$134.3 million to \$304.6 million.

For each discount rate, we present ranges of results because COBRA uses multiple health impact functions that relate PM_{2.5} and the health effects of adult mortality and non-fatal heart attacks. Therefore, there are high and low estimates of the cases avoided and their economic values for each of these health effects. The high and low estimates of the economic value of total health affects avoided are based on the corresponding high and low estimates for adult mortality and non-fatal heart attacks, along with the single estimates for all other health effects. Similarly, the high and low estimates of the economic value of all morbidity are based on the corresponding high and low estimates for non-fatal heart attacks, along with the single estimates for all other non-fatal health effects.

Table 5-3: Summary of Health Effects from Annual PM_{2.5} Reduction in 2025 (under the TMDL Scenario)

Effect / State	Incidence (Number of Cases Avoided) ³	Benefits in Thousands ⁴ (2010 \$, 2025 Income Level)	
		3% Discount Rate	7% Discount Rate
Total health effects (both morbidity and mortality, low estimate) ¹			
Delaware	N/A	\$0	\$0
District of Columbia	N/A	\$9,417	\$8,406
Maryland	N/A	\$38,362	\$34,235

¹⁶ Current EPA benefits analyses (U.S. EPA, 2006, p. 5-21) assume a 20-year lag structure, with 30 percent of premature deaths occurring in the first year, 50 percent occurring evenly over years 2 to 5 after the reduction in PM_{2.5}, and 20 percent occurring evenly over years 6 to 20 after the reduction in PM_{2.5}.

¹⁷ See the COBRA User Manual for details, available at: <http://epa.gov/statelocalclimate/documents/pdf/cobra-2.61-user-manual-july-2013.pdf>

New York	N/A	\$59,780	\$53,356
Pennsylvania	N/A	\$4,407	\$3,930
Virginia	N/A	\$3,048	\$2,721
West Virginia	N/A	\$2,697	\$2,406
Other states ²	N/A	\$35,549	\$31,713
Total	N/A	\$153,259	\$136,766
Total health effects (both morbidity and mortality, high estimate)¹			
Delaware	N/A	\$0	\$0
District of Columbia	N/A	\$21,460	\$19,141
Maryland	N/A	\$86,908	\$77,507
New York	N/A	\$134,752	\$120,195
Pennsylvania	N/A	\$9,962	\$8,882
Virginia	N/A	\$6,903	\$6,158
West Virginia	N/A	\$6,105	\$5,445
Other states ²	N/A	\$80,292	\$71,611
Total	N/A	\$346,383	\$308,939
Adult mortality (low estimate)¹			
Delaware	0.00	\$0	\$0
District of Columbia	1.04	\$9,247	\$8,236
Maryland	4.26	\$37,738	\$33,613
New York	6.63	\$58,748	\$52,326
Pennsylvania	0.49	\$4,358	\$3,881
Virginia	0.34	\$2,990	\$2,664
West Virginia	0.30	\$2,662	\$2,371
Other states ²	3.96	\$35,073	\$31,239
Total	17.02	\$150,816	\$134,329
Adult mortality (high estimate)¹			
Delaware	0.00	\$0	\$0
District of Columbia	2.39	\$21,177	\$18,862
Maryland	9.69	\$85,881	\$76,493
New York	15.00	\$132,954	\$118,420
Pennsylvania	1.11	\$9,861	\$8,783
Virginia	0.77	\$6,810	\$6,065
West Virginia	0.68	\$6,027	\$5,368
Other states ²	8.94	\$79,253	\$70,590
Total	38.58	\$341,963	\$304,581
Infant mortality			
Delaware	0.000	\$0	\$0
District of Columbia	0.004	\$45	\$45
Maryland	0.013	\$127	\$127
New York	0.015	\$143	\$143
Pennsylvania	0.001	\$5	\$5
Virginia	0.002	\$16	\$16
West Virginia	0.001	\$5	\$5
Other states ²	0.005	\$44	\$44

Total	0.040	\$385	\$385
All morbidity (low estimate)¹			
Delaware	N/A	\$0	\$0
District of Columbia	N/A	\$126	\$125
Maryland	N/A	\$497	\$495
New York	N/A	\$890	\$887
Pennsylvania	N/A	\$44	\$44
Virginia	N/A	\$41	\$41
West Virginia	N/A	\$30	\$30
Other states ²	N/A	\$432	\$430
Total	N/A	\$2,059	\$2,052
All morbidity (high estimate)¹			
Delaware	N/A	\$0	\$0
District of Columbia	N/A	\$238	\$234
Maryland	N/A	\$900	\$887
New York	N/A	\$1,655	\$1,631
Pennsylvania	N/A	\$96	\$94
Virginia	N/A	\$78	\$77
West Virginia	N/A	\$73	\$72
Other states ²	N/A	\$995	\$978
Total	N/A	\$4,034	\$3,973

¹ For each discount rate, this table contains ranges of results because COBRA uses multiple health impact functions that relate PM_{2.5} and the health effects of adult mortality and non-fatal heart attacks. Therefore, there are high and low estimates of the cases avoided and their economic values for each of these health effects. The high and low estimates of the economic value of total health affects avoided are based on the corresponding high and low estimates for adult mortality and non-fatal heart attacks, along with the single estimates for all other health effects. Similarly, the high and low estimates of the economic value of all morbidity are based on the corresponding high and low estimates for non-fatal heart attacks, along with the single estimates for all other non-fatal health effects.

² Emission reductions in the Chesapeake Bay Watershed reduces other states' ambient PM_{2.5} concentrations due to air pollution transport effects, which leads to health benefits. Other states affected by the TMDL scenario include: Alabama, Connecticut, Florida, Georgia, Louisiana, Maine, Massachusetts, New Hampshire, New Jersey, Rhode Island, and Vermont.

³ The number of deaths reported in this table is assumed to occur over 20 years as described above.

⁴ The values associated with mortality and AMI are present discounted values, discounted to 2025. This is because mortality incidence is assumed to have a 20-year lag structure and the impact of AMI was assumed to occur over multiple years as stated in the above text.

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Appendix A Detailed Inputs for Calculating Baseline and Control Emissions

Animal Population Data

Table A-1 provides the state-level animal head counts for the Chesapeake Bay Watershed for each livestock category. These data were provided at the county level by EPA's Chesapeake Bay Program Office (CBPO; based on the CBPO Watershed Model, April 2012).

Table A-1: Animal Population by Livestock Category for the Chesapeake Bay States

Livestock Categories	Delaware	Maryland	New York	Pennsylvania	Virginia	West Virginia
Angora Goats	0	416	325	1,034	1,461	231
Beef	3,634	43,835	51,193	96,756	443,959	75,837
Broilers	52,427,910	69,040,410	20,737	30,779,137	58,903,731	14,007,252
Dairy	6,211	49,496	393,398	475,038	80,818	4,680
Hogs and pigs for breeding	1,538	2,094	1,820	116,175	19,298	259
Hogs for slaughter	1,135	17,793	23,603	1,145,335	225,305	2,150
Horses	21,300	86,517	52,584	147,757	135,990	8,149
Layers	1,145,701	2,596,246	926,476	22,077,985	2,255,249	1,303,290
Milk goats	460	3,278	3,598	11,471	4,187	1,211
Other Cattle	9,600	79,887	316,202	750,658	437,971	77,595
Pullets	497,419	307,688	583,178	6,014,108	1,297,895	711,042
Sheep and lambs	869	21,688	27,567	60,059	32,904	13,169
Turkeys	714	249,665	66,186	3,770,606	11,758,313	1,664,146

Source: Obtained from EPA's CBPO based on the CBPO Watershed Model, April 2012.

Manure Management Trains

As described in Section 2.2, county-level animal numbers were apportioned to MMTs based on state-level MMT percentages obtained from Appendix C of EPA (2005a). Table A-2 lists the MMT components for each livestock type (livestock types are combinations of multiple livestock categories). Table A-3 provides MMT distributions for each livestock category by state.

Table A-2: Manure Management Train Components by Animal Type

Livestock Type	Manure Management Train	Component of System
Swine	House with Lagoon System	House with Flush, Pit Recharge, or Pull Plug pit, Solids Separator*, Solid Storage, Lagoon, and Land Application
	House with Deep Pit System	House with Deep Pit and Land Application
	Pasture/Range	Pasture/Range

Dairy	Flush Barn	Milking Center, Flush Barn, Solids Separator*, Lagoon, Dry Storage of Solids, and Land Application
	Scrape Barn	Scrape Barn Milking Center, Scrape Barn, Solids Separator*, Lagoon, Dry Storage of Solids, and Land Application
	Pasture/Range	Pasture/Range, Runoff Storage Pond, and Land Application
	Daily Spread (Scrape Barn)	Milking Center, Scrape Barn, Manure Storage Tank, and Land Application
	Barn with Deep Pit	Barn with Deep Pit Milking Center, Barn with Deep Pit, Manure Storage Tank, and Land Application
	Barn with Slurry System	Barn with Slurry System Scrape Barn with Milking, Slurry Tank/Basin, and Land Application
	Barn with Solid Storage System	Barn with Solid Storage System Barn with Milking, Dry Storage of Solids, and Land Application
Poultry	Drylot	Drylot, Storage Pond, and Land Application
	Dry Layers	Dry Layer House and Land Application
	Wet Layers	Wet Layer House, Lagoon, and Land Application
	Broiler House	Broiler House, Cake Storage, and Land Application
	Turkey House	Turkey House, Cake Storage, and Land Application
Beef	Broiler/Turkey Outdoor Confinement Area	Outdoor Confinement Area
	Feedlot	Feedlot Feedlot, Settling Basin*, Storage Pond*, Solid Storage, and Land Application
	Pasture/Range	Pasture/Range

*These components are not present at all operations. Therefore, MMTs were developed both with and without these components.

Source: EPA 2005

Table A-3: Livestock Manure Management Train Distribution by State¹ (%)

Livestock Category	Manure Management Train ²	DE	MD	NY	PA	VA	WV
Angora Goats	All	100	100	100	100	100	100
Beef	Feedlot	99.1	99.1	91.6	95.3	92	98.4
Beef	Pasture/Range	0.9	0.9	8.4	4.7	8	1.6
Broilers	House	99	99	99	99	99	99
Broilers	Outdoor Confinement	1	1	1	1	1	1
Dairy	Daily Spread	45	45	47	46	47	14
Dairy	Deep Pit	2	2	3	2	2	1
Dairy	Flush Barn	12	12	4	7	3	4
Dairy	Pasture	8	8	8	8	10	63
Dairy	Scrape Barn	10.0	10.0	10.0	12.0	7.0	5.0

Dairy	Solid Storage	23.0	23.0	28.0	25.0	31.0	13.0
Hogs and Pigs for Breeding	Breeding	100.0	100.0	100.0	100.0	100.0	100.0
Hogs for Slaughter	Deep Pit	74.0	74.0	74.0	79.0	68.0	64.5
Hogs for Slaughter	Houses with Lagoons	20.0	20.0	20.0	20.0	27.0	31.5
Hogs for Slaughter	Houses with Lagoons and Solid Sep	5.0	5.0	5.0	1.0	4.0	4.0
Hogs for Slaughter	Pasture	1.0	1.0	1.0	0.0	1.0	0.0
Horses	All	100.0	100.0	100.0	100.0	100.0	100.0
Layers	Dry Layers	95.0	95.0	95.0	95.0	100.0	95.0
Layers	Wet Layers	5.0	5.0	5.0	5.0	0.0	5.0
Milk Goats	All	100.0	100.0	100.0	100.0	100.0	100.0
Other Cattle	Daily Spread	22.50	22.50	23.50	23.00	23.50	7.00
Other Cattle	Deep Pit	1.00	1.00	1.50	1.00	1.00	0.50
Other Cattle	Feedlot	49.55	49.55	45.80	47.65	46.00	49.20
Other Cattle	Flush Barn	6.00	6.00	2.00	3.00	1.50	2.50
Other Cattle	Pasture	4.00	4.00	4.00	4.00	5.00	31.50
Other Cattle	Pasture/Range	0.45	0.45	4.20	2.35	4.00	0.80
Other Cattle	Scrape Barn	5.00	5.00	5.00	6.50	3.50	2.00
Other Cattle	Solid Storage	11.50	11.50	14.00	12.50	15.50	6.50
Pullets	House	100.0	100.0	100.0	100.0	100.0	100.0
Sheep and Lamb	All	100.0	100.0	100.0	100.0	100.0	100.0
Turkeys	House	99.0	99.0	99.0	99.0	99.0	99.0
Turkeys	Outdoor Confinement	1.0	1.0	1.0	1.0	1.0	1.0

Source: EPA (2005a)

1. The District of Columbia is not included in this table because it has no livestock.
2. When livestock category's manure management train (MMT) is listed as "all", all animals in the category are assigned to one MMT and one emissions factor.

Percentages of Controlled Animal Units and BMP Effectiveness Rates

As described in Section 3.2, we calculated ammonia emissions for the TMDL control scenario using the percentage of controlled animal units (%AU) in 2025 and BMP effectiveness rate (%reduction) in 2025. Table A-4 lists the %AU and BMP effectiveness rate in each Chesapeake Bay state for the alum and biofilters and lagoon covers BMPs.

Table A-4: Controlled Percentages of Animal Units and BMP Effectiveness Rates in Year 2025

State	Ammonia Emission Reductions BMP	%AU	% reduction
Delaware	Alum	0%	0%
	Biofilters & Lagoon Covers	10%	60%
District of Columbia	Alum	0%	0%
	Biofilters & Lagoon Covers	0%	0%
Maryland	Alum	43%	50%
	Biofilters & Lagoon Covers	0%	0%
New York	Alum	0%	0%
	Biofilters & Lagoon Covers	0%	0%
Pennsylvania	Alum	10%	15%

Virginia	Biofilters & Lagoon Covers	10%	15%
	Alum	46%	50%
West Virginia	Biofilters & Lagoon Covers	0%	0%
	Alum	0%	0%
	Biofilters & Lagoon Covers	0%	0%

Source: Chesapeake Bay watershed model inputs obtained from EPA's CBPO based on the CBPO Watershed Model, April 2012.

Appendix B Estimation of Adverse Health Effects in COBRA

Concentration-Response Functions

Table B-1 below lists the PM_{2.5}-related health endpoints and corresponding epidemiological studies EPA selected to include in this analysis. In cases where there is more than one C-R function for a pollutant/health effect combination, pooling was used to synthesize the information on two or more functions following EPA's practice. Specifically, EPA used the following pooling procedures:

- For respiratory hospital admissions (HA): Babin et al. (2007) and Sheppard (2003) estimated C-R functions for asthma hospitalizations (ICD-9 code: 493) for ages 0-18 in Washington, DC and Seattle, WA, respectively. EPA pooled the C-R functions from these two studies using the random/fixed effects method.¹⁸ EPA also pooled results from Zanobetti et al. (2009) and Kloog et al. (2012) using subjective weights pooling method (i.e., 0.5 for each study) to estimate incidence for all-respiratory admissions for the elderly (age 65 and up). EPA then aggregated incidence estimates from the following three non-overlapping categories: (1) pooled asthma hospitalization (ages 0-18) from above, (2) pooled respiratory admissions for the elderly (age 65 and up) from above, and (3) chronic obstructive pulmonary disease (COPD) for ages 18-64 from Moolgavkar (2000a).
- For HA for cardiovascular diseases less myocardial infarctions (ICD-9 codes: 390-409, 411-429): Peng et al. (2008) and Peng et al. (2009) reported C-R functions for people age 65 years and older in 108 U.S. counties and 119 U.S. urban counties, respectively. EPA assigned weights of 0.165 to the estimates from each of these two studies and weights of 0.33 to the results from each of two other studies that look at populations of 65 years and older – Zanobetti et al. (2009) and Bell et al. (2008) – and then pooled the results.
- For asthma emergency room (ER) visits, EPA pooled Mar et al. (2010), Slaughter et al. (2005), and Glad et al. (2012) using the random/fixed effects method. For asthma exacerbation, EPA pooled Ostro et al. (2001) and Mar et al. (2004). EPA first pooled results for "cough" and "shortness of breath" separately using the random/fixed effects method. EPA then assigned an equal weight (i.e., 0.33) to the pooled results for cough, the pooled results for shortness of breath, and the (un-pooled) results for wheeze (from B. Ostro, et al., 2001).

Table B-1: Summary of Studies and Concentration-Response Functions Used to Estimate PM_{2.5}-Related Benefits

¹⁸ Refer to COBRA User Manual Appendix C for explanation of the pooling methods.

Health Endpoint	Study	Location	Age Range	PM _{2.5} Coefficient (Beta)	Std. Err.
Mortality, All Cause	Krewski et al. (2009)	116 U.S. cities	30+	0.00583	0.00096
Mortality, All Cause	Lepeule et al. (2012)	6 cities	25+	0.013103	0.003347
Mortality, All Cause	Woodruff et al. (1997)	86 cities	0	0.00392	0.00122
Acute Myocardial Infarction, Nonfatal	Peters et al. (2001)	Boston, MA	18+	0.02412	0.00928
HA, All Respiratory ^a	Zanobetti et al. (2009)	26 U.S. communities	65+	0.00207	0.00045
HA, All Respiratory ^a	Kloog et al. (2012)	New England area (6 states)	65+	0.0007	0.00096
HA, Asthma ^a	Babin et al. (2007)	Washington, D.C.	0-17	0.002	0.00434
HA, Asthma ^a	Sheppard (2003)	Seattle, WA	0-17	0.00332	0.00104
HA, COPD	Moolgavkar (2000a)	Los Angeles, CA	18-64	0.0022	0.00073
HA, All Cardiovascular less Myocardial Infarction ^b	Zanobetti et al. (2009)	26 U.S. communities	65+	0.00189	0.00028
HA, All Cardiovascular less Myocardial Infarction ^b	Peng et al. (2008)	108 U.S. counties	65+	0.00071	0.00013
HA, All Cardiovascular less Myocardial Infarction ^b	Peng et al. (2009)	119 U.S. urban counties	65+	0.00068	0.00021
HA, All Cardiovascular less Myocardial Infarction ^b	Bell et al. (2008)	202 US Counties	65+	0.0008	0.00011
HA, All Cardiovascular less Myocardial Infarction ^b	Moolgavkar (2000b)	Los Angeles, CA	18-64	0.0014	0.00034
Asthma ER Visit ^c	Mar et al. (2010)	Greater Tacoma, Washington area	All	0.00560	0.00210
Asthma ER Visit ^c	Slaughter et al. (2005)	Spokane, Washington	All	0.00296	0.00271
Asthma ER Visit ^c	Glad et al. (2012)	Pittsburgh, PA	All	0.00392	0.00284
Acute Bronchitis	Dockery et al. (1996)	24 communities	8-12	0.02721	0.01710
Asthma Exacerbation, Wheeze ^d	Ostro et al. (2001)	Los Angeles, CA	6-18	0.00194	0.00080
Asthma Exacerbation, Cough ^d	Ostro et al. (2001)	Los Angeles, CA	6-18	0.00099	0.00075
Asthma Exacerbation, Shortness of Breath ^d	Ostro et al. (2001)	Los Angeles, CA	6-18	0.00257	0.00134
Asthma Exacerbation, Cough ^d	Mar et al. (2004)	Spokane, Washington	6-18	0.01906	0.00983
Asthma Exacerbation, Shortness of Breath ^d	Mar et al. (2004)	Spokane, Washington	6-18	0.01222	0.01385

Minor Restricted Activity Days	Ostro and Rothschild (1989)	Nationwide	18-64	0.00741	0.0007
Lower Respiratory Symptoms	Schwartz and Neas (2000)	6 U.S. cities	7-14	0.01901	0.00600
Upper Respiratory Symptoms	Pope et al. (1991)	Utah Valley	9-11	0.0036	0.0015
Work Loss Days	Ostro (1987)	Nationwide	18-64	0.0046	0.00036

^a These studies were pooled in COBRA to generate pooled incidence estimates for respiratory hospital admissions.

^b These studies were pooled in COBRA to generate pooled incidence estimates for cardiovascular hospital admissions.

^c These studies were pooled in COBRA to generate pooled incidence estimates for asthma-related ER visits.

^d These studies were pooled in COBRA to generate pooled incidence estimates for asthma exacerbation.

Baseline Incidence Rates (from COBRA User Manual, Appendix D)

The health impact functions used in COBRA were developed from log-linear or logistic models that estimate the percent change in an adverse health effect associated with a given pollutant change. In order to estimate the absolute change in incidence using these functions, EPA needs the baseline incidence rate of the adverse health effect. In addition, for certain health effects, such as asthma exacerbation, EPA needs a prevalence rate, which estimates the percentage of the general population with a given ailment like asthma. This section describes the data used to estimate baseline incidence rates and prevalence rates for the health effects considered in COBRA.

Mortality

This section describes the development of county mortality rates for year 2020 for use in COBRA.¹⁹ First, we describe the source of 2004-2006 individual-level mortality data and the calculation of county-level mortality rates. Then we describe how we use national-level Census mortality rate projections to develop county-level mortality rate projections for year 2020.

Mortality Data for 2004-2006

We obtained individual-level mortality data from 2004-2006 for the whole United States from the Centers for Disease Control (CDC), National Center for Health Statistics (NCHS). The data were compressed into a CD-ROM, which contains death information for each decedent, including residence county FIPS, age at death, month of death, and underlying causes (ICD-10 codes).

Using the detailed mortality data combined with U.S. Census Bureau inter-censal population estimates,²⁰ we generated age-, cause-, and county-specific mortality rates using the following formula:

¹⁹ We use projected 2020 mortality rates for year 2017 in COBRA.

²⁰ The detailed mortality data obtained from CDC do not include population. The county-level inter-censal population estimates are based on US Census of Population and Housing 2010 and forecasts developed by Woods & Poole (2011).

$$R_{i,j,k} = \frac{D_{i,j,k}(2004) + D_{i,j,k}(2005) + D_{i,j,k}(2006)}{P_{i,k}(2004) + P_{i,k}(2005) + P_{i,k}(2006)}$$

where $R_{i,j,k}$ is the mortality rate for age group i , cause j , and county k ; D is the death count; and P is the population.

Following CDC Wonder (<http://wonder.cdc.gov>), we treated mortality rates as “unreliable” when the death count is less than 20.²¹ For each combination of age group and mortality cause, we used the following procedure to deal with the problem of “unreliable” rates:

- For a given state, we grouped the counties where the death count (i.e., the numerator on the right-hand side of the above equation) was less than 20 and summed those death counts across those counties. If the sum of deaths was greater than or equal to 20, we then summed the populations in those counties, and calculated a single rate for the “state collection of counties” by dividing the sum of deaths by the sum of populations in those counties. This rate was then applied to each of those counties.²²
- If the sum of deaths calculated in the above step was still less than 20, the counties in the “state collection of counties” were not assigned the single rate from the above step. Instead, we proceeded to the regional level (see Table B-2 for region definition). In each region, we identified all counties whose death counts were less than 20 (excluding any such counties that were assigned a rate in the previous step). We summed the death counts in those counties. If the sum of deaths was greater than or equal to 20, we then summed the populations in those counties, and calculated a single rate for the “regional collection of counties” by dividing the sum of deaths by the sum of populations in those counties. This rate was then applied to each of those counties in the “regional collection of counties.”²³

Table B-2. Regional Definitions from U.S. Census

Region	States Included
Northeast	Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, Pennsylvania
Midwest	Ohio, Indiana, Illinois, Michigan, Wisconsin, Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas
South	Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida, Kentucky, Tennessee, Alabama, Mississippi, Arkansas, Louisiana, Oklahoma, Texas

²¹ Among all the calculated age-, cause-, and county-specific mortality rates, there were about 67% “unreliable” rates.

²² After this adjustment, there were 17% unreliable rates left.

²³ After this regional adjustment, there were 7% unreliable rates left.

West

Montana, Idaho, Wyoming, Colorado, New Mexico, Arizona, Utah, Nevada, Washington, Oregon, California, Alaska, Hawaii

- If the sum of deaths calculated in the previous (regional) step was still less than 20, the counties in the “regional collection of counties” were not assigned the single rate from the above step. Instead, we proceeded to the national level, identifying all counties in the nation whose death counts were less than 20 (excluding any such counties that were assigned a rate in the previous steps). We summed the death counts in those counties and divided by the sum of the populations in those counties to derive a single rate for the “national collection of counties.” This rate was then applied to each of those counties in the “national collection of counties.”²⁴

Table B-3. National All-Cause Mortality Rates (per 100 people per year) by Age Group

Mortality Category	Infant*	1—17	18--24	25--34	35--44	45--54	55--64	65--74	75--84	85+
Mortality, All Cause	0.241	0.028	0.089	0.106	0.194	0.430	0.902	2.126	5.234	14.654

* We estimate post-neonatal mortality (deaths after the first month) for infants because the health impact function (see Appendix C of the COBRA User Manual) estimates post-neonatal mortality.

Mortality Rate Projections to 2020

To estimate age- and county-specific mortality rates in year 2020, we calculated adjustment factors, based on a series of Census Bureau projected national mortality rates (for all-cause mortality), to adjust the age- and county-specific mortality rates calculated using 2004-2006 data as described above. We used the following procedure:

- For each age group, we obtained the series of projected national mortality rates from 2005 to 2050 (see the 2005 rate in Table B-4) based on Census Bureau projected life tables.²⁵
- We then calculated, separately for each age group, the ratio of Census Bureau national mortality rate in year 2020 to the 2005 rate. These ratios are shown in Table B-5.
- Finally, to estimate mortality rates in year 2020 that are both age group-specific and county-specific, we multiplied the county- and age-group-specific mortality rates for 2004-2006 by the appropriate ratio calculated in the previous step. For example, to estimate the projected mortality rate in 2020 among ages 18-24 in Wayne County, MI, we multiplied the mortality rate for ages 18-24 in Wayne County in 2004-2006 by the ratio of Census Bureau projected national mortality rate in 2020 for ages 18-24 to Census Bureau national mortality rate in 2005 for ages 18-24.

²⁴ Even after this national adjustment, there were about 1% unreliable rates left. In these cases, we simply calculated a single rate for the “national collection of counties, even though it was “unreliable,” and assigned it to those counties in the “national collection of counties.”

²⁵ For a detailed description of the model, the assumptions, and the data used to create Census Bureau projections, see the working paper, "Methodology and Assumptions for the Population Projections of the United States: 1999 to 2100, Working Paper #38.", which is available on <http://www.census.gov/population/www/documentation/twps0038/twps0038.html> (Hollman, et al. 2000) .

Table B-4. All-Cause Mortality Rate (per 100 people per year), by Source, Year, and Age Group

Source & Year	Infant*	1-17	18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
Calculated CDC 2004-2006	0.684/0.230	0.028	0.089	0.106	0.194	0.430	0.902	2.126	5.234	14.654
Census Bureau 2005	0.654	0.029	0.088	0.102	0.183	0.387	0.930	2.292	5.409	13.091

* The Census Bureau estimate is for all deaths in the first year of life. COBRA uses post-neonatal mortality (deaths after the first month, i.e., 0.23 per 100 people) because the health impact function (see Appendix C of the COBRA User Manual) estimates postneonatal mortality. For comparison purpose, we also calculated the rate for all deaths in the first year, which is 0.684 per 100 people).

Table B-5. Ratio of 2020 All-Cause Mortality Rate to 2005 Estimated All-Cause Mortality Rate, by Age Group

Year	Infant	1--17	18--24	25--34	35--44	45--54	55--64	65--74	75--84	85+
2020	0.85	0.81	0.86	0.90	0.83	0.85	0.87	0.85	0.83	0.91

Hospitalizations

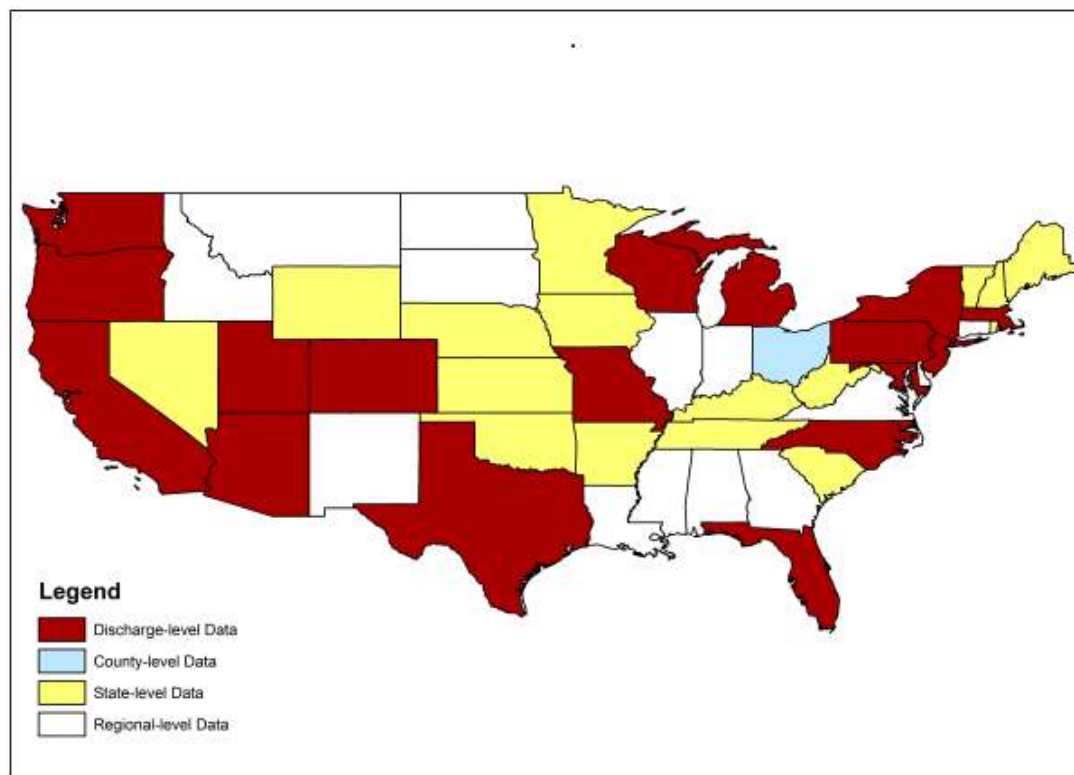
Hospitalization rates were calculated using data from the Healthcare Cost and Utilization Project (HCUP). HCUP is a family of health care databases developed through a Federal-State-Industry partnership and sponsored by the Agency for Healthcare Research and Quality (AHRQ).²⁶ HCUP products include the State Inpatient Databases (SID), the State Emergency Department Databases (SEDD), the Nationwide Inpatient Sample (NIS), and the Nationwide Emergency Department Sample (NEDS). HCUP databases can be obtained from the following data services:

- The HCUP Central Distributor: Many of the HCUP databases are available for purchase through the HCUP Central Distributor. The databases include detailed information for individual discharges, such as primary diagnosis (in ICD-9 codes), patient's age and residence county.
- HCUP State Partners: Some HCUP participating states do not release their data to the Central Distributor; however, the data may be obtained through contacting the State Partners. Some State Partners (e.g., CA, TX, and NY) provided discharge-level data; others (e.g., OH) provided summarized data.
- HCUPnet: This is a free, on-line query system based on data from HCUP. It provides access to summary statistics at the state, regional and national levels.

Exhibit B-1 shows the level of hospitalization data (e.g, discharge-level or state-level) for each state. Note that for some states neither discharge-level nor state-level data were available. In such cases we used regional statistics from HCUPnet to estimate hospitalization rates for those states.

²⁶ More information about HCUP can be found at <http://www.hcup-us.ahrq.gov/>.

Exhibit B-1. Hospitalization Data from HCUP



The procedures for calculating hospitalization rates are summarized as follows:²⁷

- For states with discharge-level data:
 - We calculated age-, health endpoint-, and county-specific hospitalization counts.²⁸
 - The above calculation excluded hospitalizations with missing patient age or county FIPS, which may lead to underestimation of rates. Therefore we scaled up the previously calculated age-, endpoint-, and county-specific counts using an adjustment factor obtained as follows:
 - We first counted the number of discharges for a specific endpoint in the state **including** those discharges with missing age or county FIPS.
 - We then counted the number of discharges for the endpoint in the state **excluding** those records with missing age or county FIPS.
 - The adjustment factor is the ratio of the two counts.
 - We calculated hospitalization rates for each county by dividing the adjusted county-level hospitalization counts by the Census estimated county-level population for the corresponding year (2006 or 2007). Following CDC Wonder, we treated rates as

²⁷ The data year for most states is 2007; the exception is MA, for which the data year is 2006. We assume hospitalization rates are reasonably constant from 2006-2007 and consider all as 2007 rates.

²⁸ Ohio was the only state that, while not providing discharge-level data, did provide county-level data for each age group-endpoint combination.

“unreliable” when the hospitalization count was less than 20, using the same procedure we used for mortality rates above.

- For states with summarized state statistics (from HCUPnet) we calculated the state-, age-, endpoint- specific hospitalization rates and applied them to each county in the state. We used the previously described procedure to adjust the “unreliable” rates.
- For states without discharge-level or state-level data:
 - We obtained the endpoint-specific hospitalization counts in each region from HCUPnet/NIS (we refer to this count for the i th endpoint in the j th region as “ $TOTAL_{ij}$ ”)
 - For those states in the j th region that do have discharge-level or state-level data, we summed the hospital admissions by endpoint (we refer to this count for the i th endpoint in the j th region as “ SUB_{ij} ”).
 - We then estimated the hospitalization count for states without discharge or state data for the i th endpoint in the j th region as $TOTAL_{ij} - SUB_{ij}$. Note that while this count is endpoint- and region- specific, it is not age-specific. We obtained the distribution of hospital admission counts across age groups based on the National Hospital Discharge Survey (NHDS) and assumed the same distribution for the HCUP hospitalizations. We then applied this distribution to the estimated hospital counts (i.e., $TOTAL_{ij} - SUB_{ij}$) to obtain endpoint-, region-, and age-specific counts.
 - Using the corresponding age- and region-specific populations, we calculated age-specific hospitalization rates for the i th endpoint in the j th region and applied them to those counties in the region that didn’t have discharge-level or state-level data.

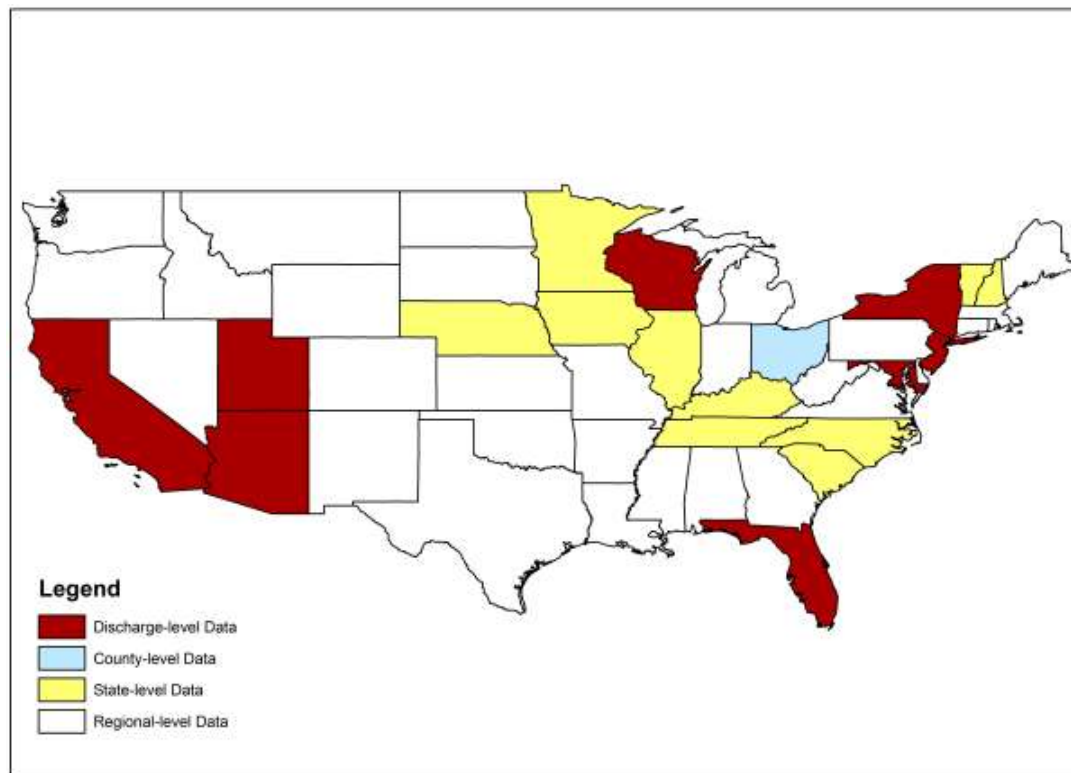
Table B-6. National Hospitalization Rates, by Health Endpoint and Age Group

Hospitalization Category	ICD-9 Codes	Hospitalization Rate by Age Group (admissions per 100 people per year)				
		0-17	18-44	45-64	65-84	85+
Respiratory						
All respiratory	460-519	0.700	0.288	0.995	3.73	8.352
Asthma	493	0.173	0.068	0.145	0.216	0.325
Chronic lung disease	490-496	0.178	0.089	0.381	1.21	1.598
Cardiovascular						
All cardiovascular (less AMI)	390-409, 411-430	0.019	0.234	1.356	4.974	10.051

Emergency Room Visits for Asthma

The data source for emergency department/room (ED or ER) visits is also HCUP, i.e., SID, SEDD, and NEDS. And the types of data providers are also the same as those described above for hospitalizations. Exhibit B-2 shows the emergency department data in each state.

Exhibit B-2. Emergency Department Data from HCUP



The calculation of ER visit rates is also similar to the calculation of hospitalization rates, except for the following differences:

- The SEDD databases include only those ER visits that ended with discharge. To identify the ER visits that ended in hospitalization, we used a variable called “admission source” in the SID databases. Admission source identified as “emergency room” indicates that the hospital admission came from the ER – i.e., the ER visit ended in hospitalization. For each combination of age group, endpoint and county, we summed the ER visits that ended with discharge and those that resulted in hospitalization.
- The data year varies across the states from 2005 to 2007 (see Table B-7); we assumed that ER visit rates are reasonably constant across these three years and consider them as 2006 rates.
- Instead of using HCUPnet/NIS and NHDS in the last step as described for hospitalizations, we used HCUPnet/NEDS and the National Ambulatory Medical Care Survey (NAMCS) to calculate ER visit rates for states without discharge level or state level data.

Table B-7. National Emergency Room Visit Rates for Asthma, by Age Group

ER Category	ICD-9 Codes	ER Visit Rate (visits per 100 people per year)				
		0-17	18-44	45-64	65-84	85+
Asthma	493	0.860	0.573	0.393	0.248	0.308

Nonfatal Heart Attacks

The relationship between short-term particulate matter exposure and heart attacks was quantified in case-crossover analyses by Peters et al (2001), Pope et al. (2006), and Sullivan et al. (2005). The study population was selected from heart attack survivors in a medical clinic. Therefore, the applicable population to apply to the C-R function is all individuals surviving a heart attack in a given year. Several data sources are available to estimate the number of heart attacks per year. For example, several cohort studies have reported estimates of heart attack incidence rates in the specific populations under study. However, these rates depend on the specific characteristics of the populations under study and may not be the best data to extrapolate nationally.

An alternative approach to the estimation of heart attack rates is to use data from the HCUP, assuming that all heart attacks that are not instantly fatal will result in a hospitalization. According to the HCUPnet, in 2009 there were approximately 633,356 hospitalizations due to heart attacks (acute myocardial infarction: ICD-9 410).²⁹ We used county-level hospitalization rates over estimates extrapolated from cohort studies because the former is part of a nationally representative survey with a larger sample size, which is intended to provide reliable national estimates. The hospitalization section above describes the detailed procedure for developing the incidence rates for hospitalization of AMI. As additional information is provided regarding the American Heart Association methodology, we will evaluate the usefulness of this estimate of heart attack incidence.

Rosamond et al. (1999) reported that approximately six percent of male and eight percent of female hospitalized heart attack patients die within 28 days (either in or outside of the hospital). We, therefore, applied a factor of 0.93 to the count of hospitalizations to estimate the number of nonfatal heart attacks per year. Table B-8 presents the national nonfatal heart attack incidence rates around year 2007 by age group (Note: county-level rates around year 2007 are used in COBRA).

Table B-8. Nonfatal Heart Attack Rates by Age Group

Endpoint	Nonfatal Heart Rate by Age Group (admissions per 100 people per year)*									
	Under 2	2-17	18-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
Non-fatal heart attack	0.000	0.000	0.009	0.016	0.066	0.200	0.352	0.626	1.020	1.728

* Rates are based on data from the 2007 HCUP/SID and an estimate from Rosamond et al. (1999) that approximately 7% of individuals hospitalized for a heart attack die within 28 days.

Other Acute Effects

For many of the minor effect studies, baseline rates from a single study are often the only source of information, and we assume that these rates hold for locations in the U.S. The use of study-specific estimates are likely to increase the uncertainty around the estimate because they are often estimated from a single location using a relatively small sample. These endpoints include: acute bronchitis, upper respiratory symptoms, lower respiratory symptoms. Table B-9 presents a summary of these baseline rates.

²⁹ Source: Online query on HCUPnet website accessed 1-13-2012

<http://hcupnet.ahrq.gov/HCUPnet.app/HCUPnet.jsp?Id=53F290DC050F1296&Form=SelLAY&GoTo=MAINSEL&JS=Y>

Table B-9. Selected Acute Effects Rates

Endpoint	Age	Parameter	Rate	Source
Acute Bronchitis	8-12	Incidence	4.300	(American Lung Association, 2002, Table 11)
Lower Respiratory Symptoms (LRS)	7-14	Incidence	43.8	(Schwartz et al., 1994, Table 2)
Minor Restricted Activity Days (MRAD)	18-64	Incidence	780.0	(B. D. Ostro & Rothschild, 1989, p. 243)
Work Loss Day (WLD)	18-64	Incidence	217.2	(Adams, Hendershot, & Marano, 1999, Table 41); (U.S. Bureau of the Census, 1997)

Acute Bronchitis

The annual rate of acute bronchitis for children ages 5 to 17 was obtained from the American Lung Association (2002). The authors reported an annual incidence rate per person of 0.043, derived from the 1996 National Health Interview Survey.

Lower Respiratory Symptoms

Lower respiratory symptoms (LRS) are defined as two or more of the following: cough, chest pain, phlegm, wheeze. The proposed yearly incidence rate for 100 people, 43.8, is based on the percentiles in Schwartz et al (1994, Table 2). The authors did not report the mean incidence rate, but rather reported various percentiles from the incidence rate distribution. The percentiles and associated per person per day values are 10th = 0 percent, 25th = 0 percent, 50th = 0 percent, 75th = 0.29 percent, and 90th = 0.34 percent. The most conservative estimate consistent with the data are to assume the incidence per person per day is zero up to the 75th percentile, a constant 0.29 percent between the 75th and 90th percentiles, and a constant 0.34 percent between the 90th and 100th percentiles. Alternatively, assuming a linear slope between the 50th and 75th, 75th and 90th, and 90th to 100th percentiles, the estimated mean incidence rate per person per day is 0.12 percent.³⁰ We used the latter approach in this analysis, and then multiplied by 100 and by 365 to calculate the incidence rate per 100 people per year.

Minor Restricted Activity Days (MRAD)

Ostro and Rothschild (1989, p. 243) provide an estimate of the annual incidence rate of MRADs (7.8). We multiplied this estimate by 100 to get an annual rate per 100 people.

Work Loss Days

The yearly work-loss-day incidence rate per 100 people is based on estimates from the 1996 National Health Interview Survey (Adams, et al., 1999, Table 41). They reported a total annual work loss days of 352 million for individuals ages 18 to 65. The total population of individuals of this age group in 1996 (162 million) was obtained from (U.S. Bureau of the Census, 1997). The average annual rate of work loss days per individual (2.17) was multiplied by 100 to obtain the average yearly work-loss-day rate of 217 per 100 people.

Asthma-Related Health Effects

Several studies have examined the impact of air pollution on asthma development or exacerbation in the

³⁰ For example, the 62.5th percentile would have an estimated incidence rate per person per day of 0.145 percent.

asthmatic population. Many of the baseline incidence rates used in the C-R functions are based on study-specific estimates. The baseline rates for the various endpoints are described below and summarized in Table B-10.

Table B-10. Asthma-Related Health Effects Rates

Endpoint	Age	Parameter ^a	Rate	Source
Asthma Exacerbation, Cough	6-18	Incidence	24.46	(B. Ostro, et al., 2001, p. 202) ^b
		Prevalence	14.50%	
Asthma Exacerbation, Shortness of Breath	6-18	Incidence	13.51	
		Prevalence	7.40%	
Asthma Exacerbation, Wheeze	6-18	Incidence	27.74	
		Prevalence	17.3%	
Asthma	6-18	Prevalence	10.70%	(American Lung Association, 2010), Table 7 ^c
Upper Respiratory Symptoms (URS)	9-11	Incidence	124.79	(C. A. Pope, et al., 1991, Table 2)

^a The incidence rate is the number of cases per person per year. Prevalence refers to the fraction of people that have a particular illness during a particular time period.

^b the rates in the study were for African American children of ages 8-13. We apply to children aged 6-18 to match what was used in the selected epidemiological studies.

^c The American Lung Association (2010, Table 7) estimates asthma prevalence for children 5- 17 at 10.70% (based on data from the 2008 National Health Interview Survey). We apply to ages 6-18 because what was used in the selected epidemiological studies.

Population and Income Growth Adjustments in COBRA

The unit value estimates for health effects in COBRA reflect expected growth in real income over time. This is consistent with economic theory, which argues that WTP for most goods (such as health risk reductions) will increase if real incomes increase. There is substantial empirical evidence that the income elasticity of WTP for health risk reductions is positive, although there is uncertainty about its exact value (and it may vary by health effect). Although one might assume that the income elasticity of WTP is unit elastic (e.g., a 10 percent higher real income level implies a 10 percent higher WTP to reduce health risks), empirical evidence suggests that income elasticity is substantially less than one and thus relatively inelastic. As real income rises, the WTP value also rises but at a slower rate than real income.

The effects of real income changes on WTP estimates can influence benefits estimates in two ways: through real income growth between the year a WTP study was conducted and the year for which benefits are estimated, and through differences in income between study populations and the affected populations at a particular time. Following the analysis in the 2006 PM NAAQS regulatory impact assessment (U.S. EPA, 2006), we have focused on the former.

The income adjustment in COBRA follows the approach used by EPA (2005b, p. 4-17), who adjusted the valuation of human health benefits upward to account for projected growth in real U.S. income. Faced with a dearth of estimates of income elasticities derived from time-series studies, EPA applied estimates derived from cross-sectional studies.³¹ The available income elasticities suggest that the severity of a health effect is a primary determinant of the strength of the relationship between changes in real income

and changes in WTP. As a result, EPA (2005b, p. 4-18) used different elasticity estimates to adjust the WTP for minor health effects, severe and chronic health effects, and premature mortality (see Table B-11).

Table B-11: Elasticity Values Used to Account for National Income Growth

Benefit Category	Central Elasticity Estimate
Minor Health Effect	0.14
Severe & Chronic Health Effects	0.45
Premature Mortality	0.40

In addition to elasticity estimates, projections of populations and real gross domestic product (GDP) are needed to adjust benefits to reflect real per capita income growth. COBRA uses population and GDP projections developed by EPA, which are described in EPA (2005b, p. 4-17). To estimate national population growth rates for the years between 1990 and 1999, EPA used national population estimates U.S. Census Bureau (Hollman, Mulder, & Kallan, 2000). These population estimates are based on an application of a cohort-component model to 1990 U.S. Census data projections (U.S. Bureau of the Census, 2000). For the years between 2000 and 2010, EPA applied growth rates based on the U.S. Census Bureau projections to the U.S. Census estimate of national population in 2000. EPA used projections of real GDP provided in Kleckner and Neumann (1999) for the years 1990 to 2010, and projections of real GDP (in chained 1996 dollars) provided by Standard and Poor's (2000) for the years 2010 to 2020.

Using the method outlined in Kleckner and Neumann (1999) and the population and income data described above, EPA (2005b, p. 4-18) calculated WTP adjustment factors for each of the elasticity estimates. Benefits for each of the categories (minor health effects, severe and chronic health effects, premature mortality, and visibility) are adjusted by multiplying the unadjusted benefits by the appropriate adjustment factor.

Note that because of a lack of data on the dependence of COI on income, and a lack of data on projected growth in average wages, no adjustments are made to benefits estimates based on the COI approach or to work loss days benefits estimates. This lack of adjustment would tend to result in an under-prediction of benefits in future years, because it is likely that increases in real U.S. income would also result in increased COI (due, for example, to increases in wages paid to medical workers) and increased cost of work loss days and lost worker productivity (reflecting that if worker incomes are higher, the losses resulting from reduced worker production would also be higher).

³¹ Details of the procedure can be found in Kleckner and Neumann (1999).

Appendix C Detailed Results

Table C-1 presents the detailed health effects results. Note that the avoided cases for the total health effects (both morbidity and mortality) are “N/A” because it is not appropriate to sum the incidence across different health effects.

Table C-1: Detailed Health Effects Results: TMDL Scenario

Effect / State	Incidence (Number of Cases Avoided)	Value (in thousands, 2010 \$, 2025 Income Level)	
		3% Discount Rate	7% Discount Rate
Total health effects (low estimate) ¹			
Delaware	N/A	\$0	\$0
District of Columbia	N/A	\$9,417	\$8,406
Maryland	N/A	\$38,362	\$34,235
New York	N/A	\$59,780	\$53,356
Pennsylvania	N/A	\$4,407	\$3,930
Virginia	N/A	\$3,048	\$2,721
West Virginia	N/A	\$2,697	\$2,406
Other states ²	N/A	\$35,549	\$31,713
Total	N/A	\$153,259	\$136,766
Total health effects (high estimate) ¹			
Delaware	N/A	\$0	\$0
District of Columbia	N/A	\$21,460	\$19,141
Maryland	N/A	\$86,908	\$77,507
New York	N/A	\$134,752	\$120,195
Pennsylvania	N/A	\$9,962	\$8,882
Virginia	N/A	\$6,903	\$6,158
West Virginia	N/A	\$6,105	\$5,445
Other states ²	N/A	\$80,292	\$71,611
Total	N/A	\$346,383	\$308,939
Adult mortality (high estimate) ¹			
Delaware	0.00	\$0	\$0
District of Columbia	2.39	\$21,177	\$18,862
Maryland	9.69	\$85,881	\$76,493
New York	15.00	\$132,954	\$118,420
Pennsylvania	1.11	\$9,861	\$8,783
Virginia	0.77	\$6,810	\$6,065
West Virginia	0.68	\$6,027	\$5,368
Other states ²	8.94	\$79,253	\$70,590
Total	38.58	\$341,963	\$304,581
Adult mortality (low estimate) ¹			
Delaware	0.00	\$0	\$0
District of Columbia	1.04	\$9,247	\$8,236
Maryland	4.26	\$37,738	\$33,613

New York	6.63	\$58,748	\$52,326
Pennsylvania	0.49	\$4,358	\$3,881
Virginia	0.34	\$2,990	\$2,664
West Virginia	0.30	\$2,662	\$2,371
Other states ²	3.96	\$35,073	\$31,239
Total	17.02	\$150,816	\$134,329

Infant mortality

Delaware	0.000	\$0	\$0
District of Columbia	0.004	\$45	\$45
Maryland	0.013	\$127	\$127
New York	0.015	\$143	\$143
Pennsylvania	0.001	\$5	\$5
Virginia	0.002	\$16	\$16
West Virginia	0.001	\$5	\$5
Other states ²	0.005	\$44	\$44
Total	0.040	\$385	\$385

Non-fatal heart attacks (low estimate)¹

Delaware	0.00	\$0	\$0
District of Columbia	0.11	\$14	\$13
Maryland	0.39	\$49	\$48
New York	0.76	\$93	\$90
Pennsylvania	0.05	\$6	\$6
Virginia	0.04	\$4	\$4
West Virginia	0.04	\$5	\$5
Other states ²	0.56	\$68	\$66
Total	1.96	\$239	\$233

Non-fatal heart attacks (high estimate)¹

Delaware	0.00	\$0	\$0
District of Columbia	1.03	\$126	\$122
Maryland	3.64	\$453	\$439
New York	7.04	\$858	\$834
Pennsylvania	0.48	\$58	\$56
Virginia	0.33	\$41	\$40
West Virginia	0.40	\$49	\$47
Other states ²	5.23	\$631	\$614
Total	18.14	\$2,215	\$2,153

Respiratory-related hospitalizations

Delaware	0.00	\$0	\$0
District of Columbia	0.28	\$7	\$7
Maryland	1.25	\$32	\$32
New York	2.28	\$57	\$57
Pennsylvania	0.11	\$3	\$3
Virginia	0.09	\$2	\$2
West Virginia	0.11	\$3	\$3
Other states ²	1.22	\$33	\$33

Total	5.34	\$138	\$138
Cardiovascular-related hospitalizations			
Delaware	0.00	\$0	\$0
District of Columbia	0.38	\$15	\$15
Maryland	1.61	\$63	\$63
New York	2.84	\$110	\$110
Pennsylvania	0.15	\$6	\$6
Virginia	0.12	\$5	\$5
West Virginia	0.11	\$4	\$4
Other states ²	1.55	\$60	\$60
Total	6.76	\$263	\$263
Acute bronchitis			
Delaware	0.00	\$0	\$0
District of Columbia	1.13	\$1	\$1
Maryland	6.55	\$3	\$3
New York	10.95	\$5	\$5
Pennsylvania	0.48	\$0	\$0
Virginia	0.52	\$0	\$0
West Virginia	0.31	\$0	\$0
Other states ²	5.16	\$3	\$3
Total	25.09	\$12	\$12
Episodes of upper respiratory symptoms (runny or stuffy nose; wet cough; and burning, aching, or red eyes)			
Delaware	0.00	\$0	\$0
District of Columbia	20.44	\$1	\$1
Maryland	119.24	\$4	\$4
New York	199.85	\$7	\$7
Pennsylvania	8.72	\$0	\$0
Virginia	9.38	\$0	\$0
West Virginia	5.58	\$0	\$0
Other states ²	94.42	\$3	\$3
Total	457.65	\$15	\$15
Episodes of lower respiratory symptoms (cough, chest pain, phlegm, or wheeze)			
Delaware	0.00	\$0	\$0
District of Columbia	14.45	\$0	\$0
Maryland	83.85	\$2	\$2
New York	152.53	\$3	\$3
Pennsylvania	6.46	\$0	\$0
Virginia	6.42	\$0	\$0
West Virginia	3.94	\$0	\$0
Other states ²	76.84	\$1	\$1
Total	344.49	\$7	\$7
Asthma-related emergency room visits			
Delaware	0.00	\$0	\$0
District of Columbia	0.48	\$0	\$0

Maryland	4.09	\$2	\$2
New York	8.30	\$4	\$4
Pennsylvania	0.24	\$0	\$0
Virginia	0.17	\$0	\$0
West Virginia	0.10	\$0	\$0
Other states ²	2.19	\$1	\$1
Total	15.56	\$7	\$7

Minor restricted activity days (days on which activity is reduced, but not severely restricted)

Delaware	0.00	\$0	\$0
District of Columbia	912.15	\$63	\$63
Maryland	3,547.73	\$244	\$244
New York	6,334.85	\$436	\$436
Pennsylvania	294.43	\$20	\$20
Virginia	297.41	\$20	\$20
West Virginia	174.47	\$12	\$12
Other states ²	2,728.98	\$188	\$188
Total	14,290.01	\$984	\$984

Work days lost due to illness

Delaware	0.00	\$0	\$0
District of Columbia	159.61	\$24	\$24
Maryland	601.18	\$91	\$91
New York	1,076.08	\$162	\$162
Pennsylvania	49.08	\$7	\$7
Virginia	50.95	\$8	\$8
West Virginia	29.15	\$4	\$4
Other states ²	454.37	\$69	\$69
Total	2,420.41	\$365	\$365

Asthma exacerbations

Delaware	0.00	\$0	\$0
District of Columbia	21.77	\$1	\$1
Maryland	125.78	\$7	\$7
New York	210.90	\$12	\$12
Pennsylvania	9.36	\$1	\$1
Virginia	10.09	\$1	\$1
West Virginia	5.95	\$0	\$0
Other states ²	99.81	\$6	\$6
Total	483.66	\$28	\$28

1. For each discount rate, this table contains ranges of results because COBRA uses multiple health impact functions that relate PM_{2.5} and the health effects of adult mortality and non-fatal heart attacks. Therefore, there are high and low estimates of the cases avoided and their economic values for each of these health effects. The high and low estimates of the economic value of total health affects avoided are based on the corresponding high and low estimates for adult mortality and non-fatal heart attacks, along with the single estimates for all other health effects. Similarly, the high and low estimates of the economic value of all morbidity are based on the corresponding high and low estimates for non-fatal heart attacks, along with the single estimates for all other non-fatal health effects.

2. Emission reductions in the Chesapeake Bay Watershed reduces other states' ambient PM_{2.5} concentrations due to air pollution transport effects, which leads to health benefits. Other states affected by the TMDL scenario include: Alabama, Connecticut, Florida, Georgia, Louisiana, Maine, Massachusetts, New Hampshire, New Jersey, Rhode

Island, and Vermont.